Co-Voting Patterns in the Dutch Parliament: A Social Network Analysis Approach

Group 17

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1 Introduction

Over the past decades, the Dutch political landscape has become one of the most fragmented in Europe. With 54 different parties officially registered, of which 15 currently hold seats in the Dutch House of Representatives. This growing fragmentation has made it increasingly difficult to form a stable majority coalition (Otjes & Louwerse, 2015). Moreover, the repeated collapses of Dutch governments since 2017 illustrate a deeper tension in Dutch politics. As the number of viable parties increases, the ideological distances between them appear to widen. This makes both coalition formation and long-term cooperation increasingly fragile.

Against this background, the aim of this study is to analyze the co-voting patterns between political parties with regard to proposed motions in the Dutch House of Representatives during the 2023-2024 election cycle. Specifically, it investigates whether these patterns can provide insights into underlying trends of political cooperation, polarization among parties. By applying social network analysis techniques, it seeks to uncover potential preferential alignment between political parties. Furthermore, it explores whether political parties tend to support motions proposed by certain parties more frequently as elections approach and a new coalition is formed.

This paper is divided into two studies. The first study will analyze whether ideological distance, measured along both the left-right and conservative-progressive dimensions, explains variation in co-voting similarity between parties. It will do so by answering the following research question:

> *RQ1: How does ideological distance between Dutch political parties affect their voting similarity?*

The hypothesis for this research question in the following:

> *H1: Dutch political parties that are ideologically closer will show higher voting similarity.*

Ideological distance on the left-right continuum is widely recognized as a key explanatory factor for inter-party cooperation and voting similarity (Fowler, 2006). While most research describes party ideology along a one-dimensional left-right axis, party ideology in the Netherlands is also often captured along a conservative-progressive dimension. This study contributes to the literature by examining whether this second dimension helps explain voting similarity between members of parliament represented by parties in the Dutch parliament. It does this by applying a Multiple Regression Quadratic Assignment Procedure (MRQAP) to test whether ideological proximity on both the left-right and conservative-progressive axes is associated with higher inter-party voting similarity.

The second study of this paper will focus on analyzing how co-voting patterns between Dutch political parties change during the election cycle. It compares three co-voting networks representing distinct stages of the election cycle: one constructed from votes far from the election in 2023, one close to the election, and one after coalition formation. This study will answer the following research question:

RQ2: How do co-voting patterns between Dutch political parties change during the election cycle?

As argued by Otjes and Louwerse (2015), voting similarity captures both ideological proximity, as the strategic considerations involved in coalition formation. Studying how these co-voting patterns change around elections can therefore help to identify whether parties adjust their support to signal possible cooperation. To answer this research question, an ERGM with weighted, undirected edges will be used, where an edge from Party A to Party B represents the number of motions on which both parties voted the same way. The following table presents the formulated hypotheses and the corresponding ERGM terms.

Hypothesis	ERGM Term	Motivation
H1: As elections approach, co-voting networks show higher degree of centralisation.	`kstar`	The k-star term captures to what extend a small number of parties maintain voting ties with many others. Comparing this parameter across election phases reveals whether co-voting becomes more centralised when elections approach. A possible sign that some parties increase their cross-party alignment to maximise coalition opportunities.
H2: If Party A votes similarly to Party B and Party B votes similarly to Party C, Party A is more likely to vote similarly to Party C as elections approach.	`gwesp`	The gwesp term can measure whether co-voting behavior tends to form triads. This can be informative for explaining coalition potential with respect to voting behavior.
H3: Parties that have the potential to form a coalition, even if ideologically distant, are more likely to increase co-voting in the run-up to elections.	`edgecov(coalition_ opportunity × absdiff(ideology) x time_to_election)`	The absdiff term captures how the political ideology distance influences co-voting patterns. The interaction with coalition opportunity examines whether co-voting increases despite ideological distance when there is an opportunity for parties to form a coalition.

Hypothesis	ERGM Term	Motivation
H4: Parties that have been in a coalition before are more likely to show stronger co-voting patterns, and this effect intensifies closer to the election.	`edgecov(same_coalition_before x time_to_election)`	The edgecov term captures the extent to which ties between parties with regards to having been in the coalition before influences the tie formation in the context of co-voting patterns.

2 Dataset

2.1 Data Source and Collection

The data used in this analysis is retrieved from the Open Data Portal of the Dutch House of Representatives (Tweede Kamer der Staten-Generaal, 2024), a freely accessible repository providing transparency about parliamentary activities. The portal contains voting records, parliamentary documents, and member information through an OData API that has been set up since 2008. The parliamentary data system integrates four primary sources: Parlis (parliamentary documents including motions and voting results), Sesam (MP data and party affiliations), VLOS (detailed meeting reports), and Toezeggingenregistratie (ministerial commitments). These systems continuously add to the parliamentary Data Warehouse, making sure there is transparency in all parliamentary activities.

For our analysis, we focus on the period 2023-2024, covering the electoral cycle surrounding the November 22, 2023 general election and the following cabinet formation on July 2, 2024. Voting data were extracted via automated API queries using R (version 4.x), filtering for Voor (Yes) and Tegen (No) votes only, with absent votes excluded. The data collection was performed in October 2025, so all voting records are up to date.

To enrich the dataset for Study 1, we combine the parliamentary voting data with ideological positioning data from Kieskompas (ProDemos and Kieskompas, 2023), a widely-used tool during Dutch elections that maps party positions on policy issues. For the 2023 election, we extract party positions from Kieskompas visualizations, mapping them to normalized scales for left-right economic ideology and progressive-conservative cultural ideology. This combination of datasets allows us to examine how ideological distance influences voting similarity.

2.2 Network Construction

We build party co-voting networks where nodes represent political parties (fracties) and edges represent co-voting relationships. For parties i and j, the raw edge weight is defined as:

$$w_{ij} = \# \text{ motions where } i, j \text{ both voted the same (Yes/No)}$$

Additionally, we compute the agreement rate: $\text{Agreement rate}_{ij} = w_{ij}/\#$ motions where i, j both voted, which we report as a descriptive statistic. Edges are created only when both parties voted on at least 5 shared motions to ensure reliability. This construction yields one weighted, undirected party-party network for every electoral cycle period.

2.3 Temporal Periods

To study electoral cycle dynamics, we devide the data into three periods that align with political events:

Table 2: Temporal Periods and Political Context

Period	Timeframe	Duration	Context
Far from Election	Q1+Q2 2023 (Jan 20 – Jun 29)	160 days	Normal operations (Rutte IV)
Close to Election	Q3+Q4 2023 (Jul 5 – Nov 13)	131 days	Campaign; election Nov 22
Post Formation	Q3+Q4 2024 (Jul 5 – Dec 20)	168 days	New cabinet (Schoof I, Jul 2)

2.4 Descriptive Statistics

Table 3 shows voting activity across the three periods, displaying variation in parliamentary activity.

Table 3: Raw Voting Data by Period

Metric	Far	Close	Post
Duration (days)	160	131	168
Total Votes	36,788	32,756	12,821
Unique Motions	1,761	1,548	1,952
Active Parties	23	22	15
Votes per Motion	20.9	21.2	6.6
Mean Agreement Rate	63.6%	56.2%	62.2%

The Post-formation period shows a 65% reduction in total votes despite having the longest duration. Notably, agreement rates decline during the campaign period (63.6% → 56.2%), then go back up post-formation (→ 62.2%), showing already some evidence for our hypothesis about electoral cycle effects.

Table 4 shows network-level statistics, where we can see how party cooperation patterns differ across periods.

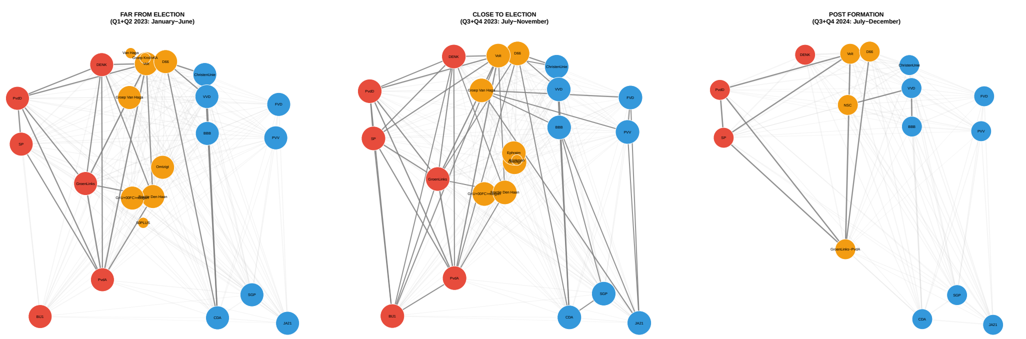
Table 4: Network Structure Comparison

Metric	Far	Close	Post
Nodes (parties)	23	22	15
Edges	190	210	105
Density	0.75	0.91	1.00
Mean Degree	16.5	19.1	14.0
Components	4	2	1
Mean Edge Weight	1,123	862	201

Network density keeps on increasing (0.75 → 1.00), with the Post-formation network having complete connectivity. However, mean edge weights drop by 82% from Far to Post, showing normalization is necessary for good cross-period comparison.

Figure 1 shows the three party co-voting networks visualized with ideological positioning. Node colors represent ideological spectrum (red = left, orange = center, blue = right), node size reflects degree centrality, and edge thickness represents cooperation strength.

Figure 1: Party Co-voting Networks Across the Electoral Cycle (Raw Weights). Edges shown are 30% above mean weight for visual clarity.



2.4.1 Z-Score Normalization

The dramatic variation in voting volume makes raw edge weights incomparable across periods. To address this, we apply z-score standardization within each period:

$$z_{ij}^{(t)} = \frac{w_{ij}^{(t)} - \mu^{(t)}}{\sigma^{(t)}}$$

where $w_{ij}^{(t)}$ is the raw weight in period t, and $\mu^{(t)}$, $\sigma^{(t)}$ are the mean and standard deviation of all edge weights in that period. This transforms each period to $\mu = 0$, $\sigma = 1$, making sure we can compare relative cooperation patterns rather than absolute volumes. Values of

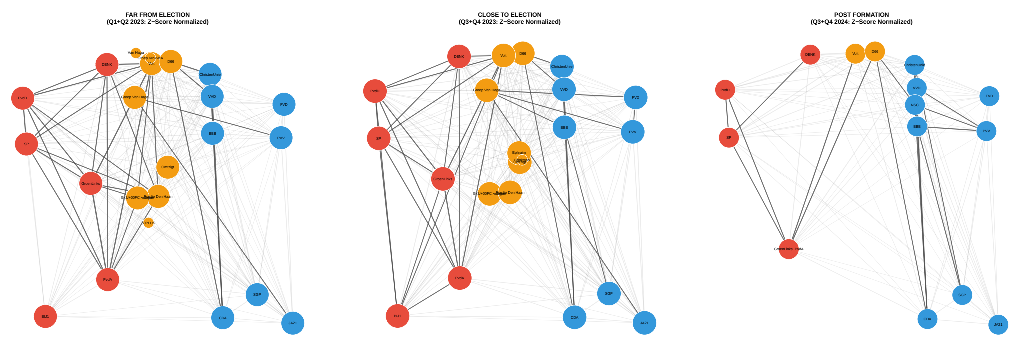
$z > 1.0$ indicate above-average cooperation (84th percentile), while $z > 2.0$ indicates very strong cooperation (97.5th percentile).

Table 5: Z-Score Normalized Edge Statistics

Metric	Far	Close	Post
Total Edges	190	210	105
Strong Ties (z>1)	32	33	21
% Strong Ties	16.8%	15.7%	20.0%
Very Strong (z>2)	5	1	0

Post-formation networks show the highest proportion of strong ties (20%). Figure 2 displays the z-score normalized networks, where edge prominence is determined by standardized cooperation strength rather than raw counts, allowing direct comparison across periods.

Figure 2: Z-Score Normalized Party Networks. Edge highlighting based on z > 1.0 (above-average cooperation within each period).



2.5 Vote Unanimity Validation

To validate that discovered agreement patterns show genuine party cooperation rather than unanimous votes, we analyzed vote split distributions. Table 6 shows that only 22-27% of motions are near-unanimous (90% one-sided), with 23-27% being balanced. This tells us there is good enough variation for meaningful network analysis.

Table 6: Vote Unanimity Statistics

Period	Mean Unanimity	90% Unanimous	Balanced (40-60%)
Far from Election	76.2%	26.2%	23.3%
Close to Election	73.9%	21.7%	26.6%
Post Formation	77.3%	26.8%	23.0%

2.6 Ideological Variables (Study 1)

For Study 1, party ideology is measured along two dimensions: the economic axis (left-right: redistribution vs. market orientation) and the cultural axis (progressive-conservative: liberal vs. traditional values). We extract party positions from Kieskompas 2023 visualizations , Figure 3, mapping visual coordinates to normalized scales ranging from -1 to +1 for each dimension.

Figure 3: Kieskompas 2023: Party Positions on Economic (Left-Right) and Cultural (Progressive-Conservative) Dimensions

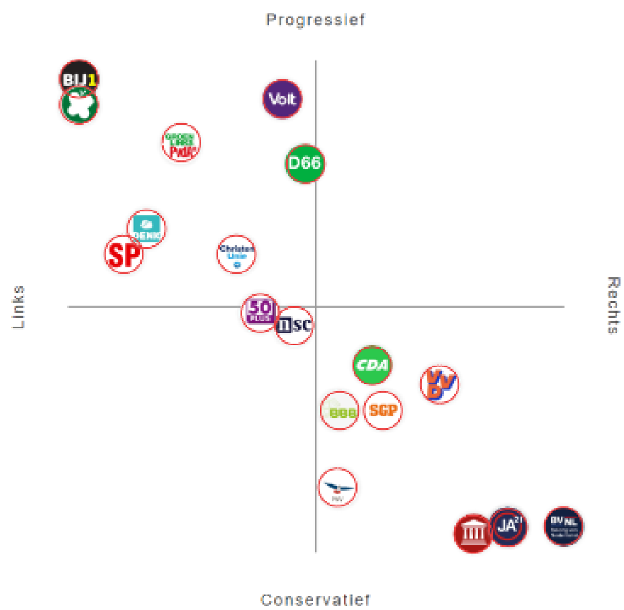


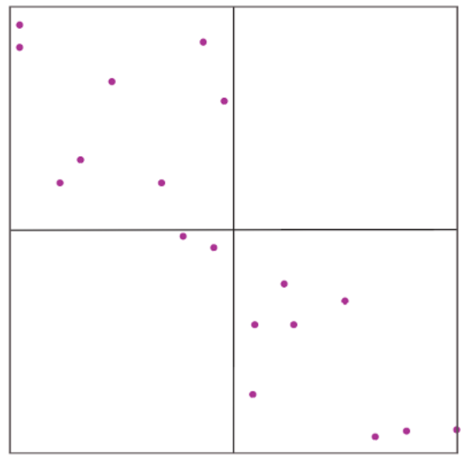
Figure 4 shows the extracted coordinate positions used in our analysis. From this visualization, we map party positions onto the two-dimensional ideological space by measuring distances between parties along both axes.

Euclidean distance between party pairs is calculated as:

$$d_{ij}^{ideology} = \sqrt{(x_i^{LR} - x_j^{LR})^2 + (x_i^{PC} - x_j^{PC})^2}$$

where x_i^{LR} is party i's left-right position and x_i^{PC} is its progressive-conservative position. These ideological coordinates will be mapped as node attributes in our network analysis for Study 1, allowing us to test whether ideological proximity on both dimensions predicts voting similarity between parties.

Figure 4: Extracted Party Coordinates from Kieskompas Visualization



2.7 Data Usefulness

This data is well-suited for studying electoral cycle dynamics and party cooperation for several reasons. First, the scraped data contains every motion voted upon attached to exact timestamps, making room for temporal analysis connected to certain electoral events. Second, the data shows preferences objectively through actual voting behavior instead of stated goals.

For Study 1, the combination of voting data and ideological measures allows us to test whether similarity in voting patterns can be explained by ideological proximity on two dimensions (economic and cultural). For Study 2, the temporal variation in voting volume and agreement rates gives us sufficient data to examine how parties might change their cooperation patterns as elections approach.

2.8 Potential Biases and Limitations

Database complexity and implicit knowledge requirements: The parliamentary database has a complicated structure with limited documentation of the underlying data model (Hug, 2010). While the general organization is explained, specific meanings of data fields often require independent research to understand correctly. This creates two main challenges. First, without clear field definitions, researchers might misuse variables, potentially introducing errors into their analysis. Second, the data contains implicit information about Dutch parliamentary procedures that may not be obvious to those unfamiliar with the system (Mikhaylov, Laver, & Benoit, 2012).

A clear example involves voting patterns: extracted vote counts often show around 20 votes per motion despite 150 parliamentary seats. This occurs because MPs from opposing parties frequently make informal agreements to both abstain (known as "pairing"), effectively canceling each other's votes (Cox & McCubbins, 2005). Without knowing this way of working, researchers might incorrectly interpret low participation rates. For our study, we address this by: (1) working with party-level data where individual abstentions matter less, (2) requiring at least 5 shared votes between parties to create edges, and (3) reading parliamentary documentation to verify our data interpretation.

Participation rate variation: The 65% drop in voting activity post-formation (36,788 votes → 12,821 votes) could reduce the reliability of some party connections and create temporal bias (Kossinets, 2006). We address this by: (1) using z-score normalization within each period, which standardizes patterns regardless of total volume, (2) requiring minimum thresholds (5 shared votes) to ensure connections are based on enough observations, and (3) analyzing each period separately rather than combining data with different participation rates.

Ideological measurement error: Kieskompas does not make public how their classification algorithm works, leaving uncertainty about which policy positions were weighted and how they were combined into the two-dimensional ideological space (Bakker et al., 2015; Louwerse & Otjes, 2012). Additionally, extracting coordinate positions from published visualizations introduces measurement error because our mapped positions try to approximate Kieskompas's outputs rather than being the true algorithm values.

These measurement issues could affect how precisely we calculate ideological distances. However, this should be manageable: (1) The error likely affects all parties the same rather than favoring certain groups, (2) we use ideology to explain voting patterns (not as our main outcome), which makes results less sensitive to measurement error, and (3) using two dimensions (economic and cultural) reveals richer ideological structure than single left-right scales, maybe making up for some imperfections. For robustness checks, alternative ideological measures (such as Chapel Hill Expert Survey or Manifesto Project data) could be used.

Temporal validity: Our ideology data from Kieskompas 2023 reflects campaign positions, while our post-formation analysis uses voting data from 2024. Party positions might have changed during coalition negotiations (Gross & Debus, 2021). However, this shift is likely small for already established parties, of which we expect the ideological positions to be the same after formation. We treat ideology as a stable node attribute.

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